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AI SOLUTIONS FOR OPTIMIZING SCRUM: PREDICTING TEAM PERFORMANCE

This study presents the development, training, and AWS cloud deployment of an AI-based assistant leveraging an LSTM network to enhance Scrum team velocity prediction. The research focuses on analyzing the assistant's interaction with key Scrum processes, highlighting its potential to optimize sprint planning and improve team performance forecasting. Through this analysis, specific sprint planning challenges suitable for AI-driven solutions were identified, paving the way for enhanced prediction accuracy and reduced uncertainty in project management. The proposed architecture outlines a logical sequence of integrated services that collectively contribute to improving Scrum process efficiency. Initial testing of a locally deployed LSTM network using a smaller dataset validated the suitability of the chosen model and confirmed its capability for accurate performance prediction. These findings establish a foundation for developing a scalable AI assistant capable of supporting Scrum teams in dynamic environments with evolving requirements. This research underscores the feasibility of applying AI technologies, particularly LSTM networks, to Scrum optimization. The results demonstrate significant potential for improving sprint planning, reducing uncertainty, and supporting adaptive project management strategies. The planned advancements in cloud-based deployment and performance evaluation will provide actionable insights into the economic and operational viability of integrating AI-driven prediction tools into real-world Scrum environments. Future work will focus on deploying the trained LSTM model in a production AWS environment to evaluate its practical performance, scalability, and operational costs. This stage will include detailed monitoring of computational resource usage and cost analysis to identify opportunities for optimization. By refining algorithmic components and improving model efficiency, we aim to enhance cost-effectiveness while maintaining high predictive accuracy.

Keywords: information system, IT project, Agile, Scrum, team velocity, AI, long short-term memory, sprint, AWS.

Introduction. The central concept in Scrum is «team velocity» – a metric that quantitatively measures the amount of work a team can complete within a sprint. Accurate team velocity forecasting is crucial as it aids in planning and resource allocation, increases predictability, and optimizes overall project management. Despite its importance, forecasting team performance remains a challenging task due to the dynamic nature of team interactions, varying task complexities, and fluctuating work capacities. Traditional forecasting methods often fall short, offering reactive rather than proactive management tools, and they lack the adaptability required to handle the nuances and changes observed in agile projects [1].

To address these issues, this study proposes the development of a system architecture for an assistant application using advanced machine learning methods, including long short-term memory (LSTM) networks. These networks are well-suited for modeling time series data and can effectively capture the long-term dependencies and nonlinear relationships inherent in team performance data.

Focusing on system architecture, this study aims to create a scalable, efficient, and effective tool that integrates seamlessly with existing Scrum management systems, enabling teams to achieve their goals in agile project management.

The assistant aims not just to predict team velocity but to act as an ever-watchful ally in the battlefield of Scrum. By seamlessly integrating with existing project management systems, the assistant enables managers and teams to focus on execution while the AI handles the predictive complexities. This intelligent tool will not only anticipate potential delays but also suggest adjustments, ensuring sprints remain on course and stakeholder confidence stays intact.

Additionally, the system's architecture is designed with scalability in mind, making it adaptable to teams of varying sizes and project scopes. Whether a startup with a scrappy five-person development team or a corporate behemoth managing dozens of teams, the assistant can efficiently process diverse datasets, learning from each iteration to provide more refined insights. The result is a forward-looking system that evolves with the team's performance patterns, offering managers a glimpse into the future with each sprint – a crystal ball of agile project management, if you will.

Analysis of recent research and publications. The concept of team velocity in Scrum is critical for project planning and evaluation. Schwaber notes [2] that traditionally, team velocity is forecasted using historical sprint data, relying on simple averages of past results. While these methods are useful, they often fail to account for variability in team composition, task complexity, and external factors, leading to inaccurate forecasts.

Ong and Uddin [3] suggest that the application of artificial intelligence will significantly expand with the advent of the new data era. Furthermore, other studies have identified specific areas where AI offers advantages, such as project management [4–7] and production management [8–9], as well as numerous fields highlighted by Heifner et al. [10], where AI can drive innovation within companies. Additionally, benefits have been demonstrated in project duration forecasting [11]. It is also worth noting that AI has proven valuable in assessing and measuring various IT strategies [12] and in developing strategic roadmaps supported by project management [13]. The article [14] highlights that active stakeholder involvement is key to aligning Scrum teams with business goals and fostering adaptability through continuous feedback.

Sima Siami-Namini et al. [15] pointed out that machine learning models, particularly those involving time series forecasting like ARIMA and LSTM networks, have shown potential in forecasting tasks that involve complex dependencies. For example, LSTM networks have been successfully used in various fields due to their ability to remember long input sequences, making them ideal for forecasting tasks where past information is crucial for future predictions. Ryabchukov [16] notes that AI methods can dynamically adapt to project changes, offering more accurate and time.

The development of a system architecture for the application of AI in project management requires a thorough analysis of data flow, processing needs, and integration capabilities. According to Zhiheng Huang [17], the architecture must support robust data acquisition mechanisms, scalable machine learning pipelines, and efficient data storage solutions. Klaus Greff et al. [18] highlight that the architecture should also facilitate continuous learning and adaptation, as the system must update its models in response to new data.lier forecasts.

Presentation of the main material. The objective of the work is to explore the potential for applying artificial intelligence to optimize Scrum methodology, focusing on the role of the AI assistant in predicting team velocity. The work aims to study how AI implementation can contribute to more efficient sprint planning, improve the accuracy of task evaluation, and optimize overall team productivity and coordination. The primary focus will be on analyzing how artificial intelligence can enhance the prediction of team potential and capabilities at various stages of project implementation.

The project goals include: (1) investigating the interaction of the AI assistant with key Scrum processes for team velocity prediction, (2) identifying sprint planning issues that AI can help address, (3) exploring AI technologies capable of optimizing Scrum process prediction and adaptation, and (4) developing the architecture of an AI assistant to improve project management efficiency within Scrum.

The application is being developed to enhance the efficiency of sprint planning and will include the following elements:

- interactivity and analytics (conversational dialogue mechanism and analytics modules allow the AI assistant to effectively collect and analyze data to optimize processes and improve team communication);
- forecasting and planning (the representative learning module and planning module use historical data and current information to accurately forecast team velocity and efficiently distribute tasks);
- resource and process optimization (the optimization module implements improvements in processes based on analytical data, helping to reduce resource and time costs for project completion);
- strategic alignment and contextualization (product vision, sprint goals, and backlog positioning provide the AI assistant with the necessary context to adapt its actions according to the strategic goals of the project).

The team velocity V, which represents the average number of completed story points per sprint, is calculated as follows:

$$V = \frac{1}{|S|} \cdot L , \tag{1}$$

where S the set of all sprints;

L the total number of story points completed across all sprints, taking into account whether each task is finished (through the σ function):

$$L = \sum_{s \in S} \sum_{t \in T_s} \text{points}(t) \cdot \sigma(\text{status}(t), c) , \tag{2}$$

where T_s – set of all tasks in sprint s;

t – represents the time required to complete task;

$\text{points}(t)$ is a function representing the number of story points assigned to task t;

σ – sigmoid function;

$\text{status}(t)$ – a function that returns the status of task t (e.g., completed, in progress, blocked);

c is s an abbreviation of «completed».

Let's describe how the LSTM model can predict team velocity based on the results of previous sprints. Suppose there are $V_1, V_2, ..., V_t$, representing the historical velocities of the team for the past sprints from 1 to n, where each V_t is measured in story points completed per sprint.

Input data (X): Typically, these are sequences of historical velocities, $\left[V_{t-n}, V_{t-n+1}, ..., V_{t-1}\right]$ where n represents the number of time periods that the LSTM model needs to consider. Output data (Y) is the team velocity for the next iteration V_t, that needs to be predicted.

The LSTM model consists of three layers that regulate the flow of information: the forget gate, the input gate, and the output gate. Each of these layers uses different weights, which the model learns during training. To describe the LSTM model, it's essential to explain each of these layers in detail. Forget gate f_t:

$$f_t = \sigma(W_f \cdot \left[h_{t-1}, x_i\right] + b_f) , \tag{3}$$

where W_f – weights of the forget gate matrix;

b_f – bias of the forget gate matrix;

h_{t-1} – previous input data;

x_t – input data at time t;

The input gate i_t and candidate cell state $\hat{C}_t$ are defined as:

$$i_t = \sigma(W_i \cdot \left[h_{t-1}, x_i + b_i\right]) , \tag{4}$$

$$\hat{C}_t = \tanh(W_C \cdot \left[h_{t-1}, x_t\right] + b_c , \tag{5}$$

where W_i та W_C – weights of the input gate matrix;

b_i та b_C – biases of the respective layers.

This layer decides which new information will be added to the cell state.

The old cell state C_t is updated to the new cell state C_t he forgets gate f_t determines what to retain from the old state, while the input gate i_t and candidate cell state $\hat{C}_t$ determine what to add:

$$C_t = f_i \cdot C_{t-1} + i_t \cdot \hat{C}_t \, . \tag{6}$$

The output gate determines what the next hidden stat (h_t), should be, which is a filtered version of the cell state. The hidden state h_t is passed to the output and used for prediction:

$$o_t = \tanh(W_0 \cdot [h_{t-1}, x_t + b_0], \tag{7}$$

$$h_t = o_t \cdot \tanh(C_t), \tag{8}$$

where W_0 – weights of the output gate matrix;

b_0 – number of tests graded.

The input data for the LSTM can include various features, such as the number of closed story points, changes in team size, or any other relevant metrics from past sprints. To create a scalable application and optimize deployment and model training time, AWS was chosen as the cloud platform [19]. To achieve good results, it is recommended to deepen the neural network and perform training on multiple GPUs, which AWS services easily facilitate.

The architecture of the assistant is shown in Fig. 1.

Amazon SageMaker will be used for deploying and training the neural network.

Data storage will be provided by the Amazon S3 service. The Amazon CloudWatch service is used for logging nearly all processes that occur between the user and the neural network.

Amazon QuickSight can be used for building graphs based on predictions and historical data. In the future, it would be beneficial to develop a separate module for data visualization.

User requests are processed using: (1) Amazon API Gateway and (2) Amazon Lambda. These services are designed to handle and execute user requests. Amazon Lambda preprocesses the requests, sends them to the SageMaker Endpoint for output, and processes the responses.

The following services are classic choices for use in high-load systems and are recommended to facilitate system scaling: (1) Amazon Elastic Load Balancer, (2) Amazon Identity and Access Management, (3) Amazon Virtual Private Cloud, and (4) Amazon Simple Queue Service. Amazon ELB distributes incoming requests to available Lambda functions for processing. Amazon Identity and Access Management ensures that only authorized entities can access or interact with services within the VPC. Amazon Virtual Private Cloud ensures that all services are within a single virtual network for security and performance. Lambda functions can enqueue messages

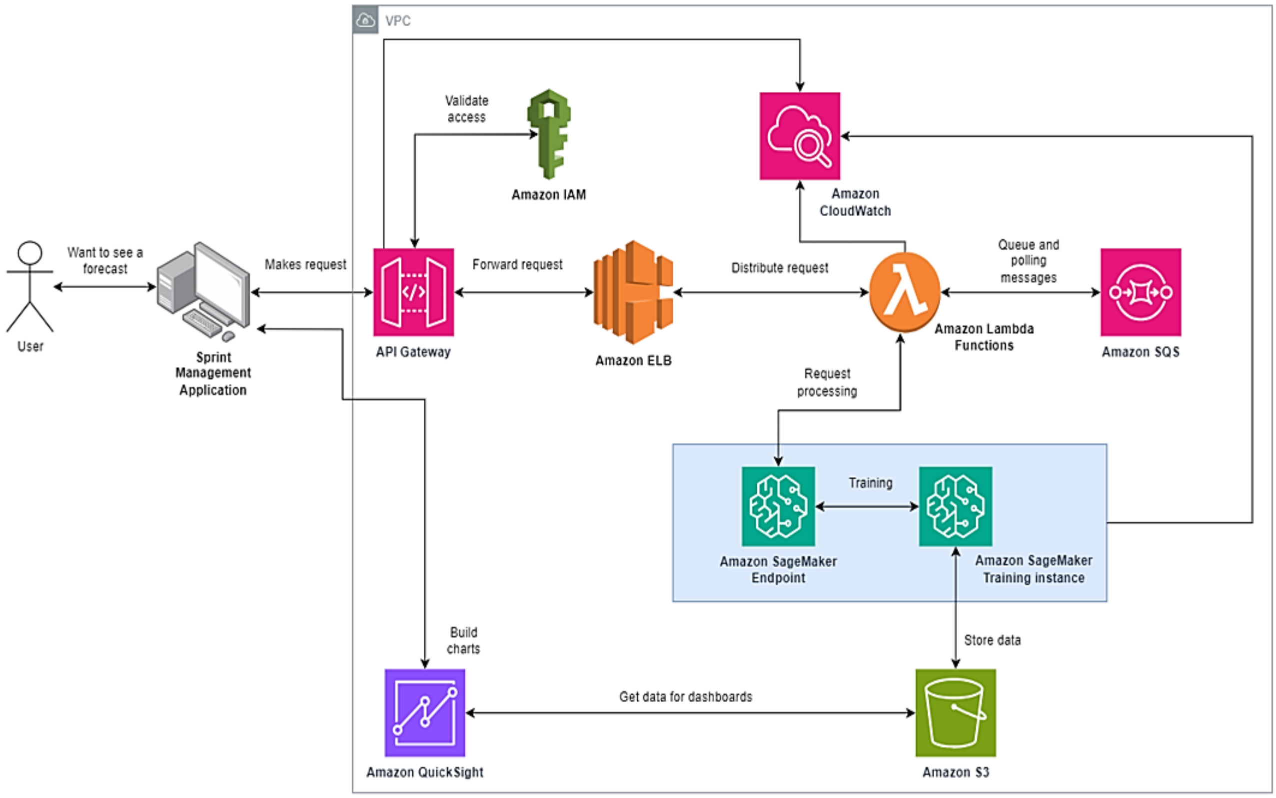

Fig. 1. Architectural diagram of the AI assistant for predicting Scrum team velocity

or data for processing and poll SQS for new messages or data to process.

To model the system's behavior, a local LSTM network was developed using the TensorFlow platform [20]. The network was trained on a dataset [21] of completed projects. This dataset contains approximately 4,200 records of project tasks, including the number of tasks, the number of story points, and the assignees for each task. Additionally, a test dataset, very similar to the Randula Koralage, of 5,000 records was generated.

Dataset contains different csv files that contains the vital information regarding tasks in sprints: Sprint ID; Status; Assignee; Current story points.

Although, Randuala's dataset contains more than 4000 records, not all of them can be used for the learning process: many records have a zero value for the current story points. For this case, we did not use those records. That is one of a reason to generate our dataset with syntactic data.

The training results of the model were as follows: (1) Precision: 93 %, (2) Recall: 10 %, (3) F-score: 84 %.

Conclusions. The architecture of the AI-based assistant, specifically using an LSTM network, has been developed, trained, and deployed in the AWS cloud to improve Scrum team velocity prediction. In the process of investigating the interaction between the assistant and key Scrum processes, the model's potential for optimizing sprint planning and predicting team performance was analyzed. Specific sprint planning issues were identified that can be addressed with AI, opening possibilities for improving prediction accuracy and reducing uncertainty in project management. AI technologies capable of enhancing the efficiency of Scrum process prediction and adaptation were explored, particularly in scenarios involving changing requirements.

The developed architecture of the AI assistant demonstrates the logical sequence of core services and their role in improving project management. A locally deployed test LSTM network with a similar architecture showed promising results on a small dataset, confirming the correctness of the model choice. Based on these outcomes, the development of a flexible and scalable AI assistant for predicting Scrum team velocity can now commence.

As a continuation of this work, the next phase will involve deploying the trained LSTM model to the AWS cloud to evaluate its performance in a production environment. This deployment will allow us to assess the computational costs associated with running the LSTM on cloud infrastructure and explore potential areas for optimization. By analyzing the resource consumption and cost dynamics, we aim to identify algorithmic adjustments or model optimizations that could improve cost efficiency without compromising predictive accuracy.

This future work will address critical aspects of scalability and operational viability, providing insights into the economic feasibility of using LSTM network for real-world SCRUM optimization.

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AI-РІШЕННЯ ДЛЯ ОПТИМІЗАЦІЇ SCRUM: ПРОГНОЗУВАННЯ ПРОДУКТИВНОСТІ КОМАНДИ

Дослідження представляє розробку, навчання та розгортання в хмарному середовищі AWS AI-асистента, що використовує мережу LSTM для підвищення точності прогнозування швидкості (velocity) команди Scrum. У роботі зосереджено увагу на аналізі взаємодії асистента з ключовими процесами Scrum, підкреслюючи його потенціал для оптимізації планування спринтів та покращення прогнозування продуктивності команди. У ході дослідження було виявлено конкретні проблеми планування спринтів, які можна вирішити за допомогою AI-рішень, що відкриває можливості для підвищення точності прогнозів і зниження рівня невизначеності в управлінні проєктами. Запропонована архітектура відображає логічну послідовність інтегрованих сервісів, які спільно сприяють підвищенню ефективності процесів Scrum. Початкове тестування локально розгорнутої мережі LSTM на невеликому наборі даних підтвердило доцільність обраної моделі та її здатність забезпечувати точне прогнозування продуктивності. Ці результати створюють основу для подальшої розробки масштабованого AI-асистента, здатного підтримувати Scrum-команди в динамічних умовах зі змінними вимогами. Це дослідження підкреслює доцільність застосування AI-технологій, зокрема мереж LSTM, для оптимізації Scrum. Результати демонструють значний потенціал у вдосконаленні планування спринтів, зменшенні невизначеності та підтримці адаптивних стратегій управління проєктами. Заплановані кроки щодо хмарного розгортання та оцінки продуктивності нададуть практичні висновки щодо економічної та операційної доцільності інтеграції інструментів AI-прогнозування в реальні Scrum-середовища. Подальші дослідження будуть зосереджені на розгортанні навченої моделі LSTM у промисловому середовищі AWS для оцінки її практичної продуктивності, масштабованості та операційних витрат. На цьому етапі планується детальний моніторинг використання обчислювальних ресурсів і аналіз витрат для виявлення можливостей оптимізації. Удосконалення алгоритмічних компонентів і підвищення ефективності моделі спрямовані на зниження витрат при збереженні високої точності прогнозування.

Ключові слова: інформаційна система, IT-проєкт, Agile, Scrum, швидкість команди, штучний інтелект, довга короткочасна пам’ять, спринт, AWS.

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